

The Analysis of Performace Model Tiered Artificial Neural Network for Assessment of Coronary Heart Disease

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ABSTRACT

The assessment model of coronary heart disease is so much developed in line with the development of information technology, particularly the field of artificial intelligence. Unfortunately, the assessment models developed mostly do not use such an approach made by the clinician, that is the tiered examination. This makes the assessment process should conduct a thorough examination. This study aims to analyze the performance of a tiered model assessment. The assessment system is divided into several levels, with reference to the stages of the inspection procedure. The method used for each level is, preprocessing, building architecture artificial neural network (ANN), conduct training using the Levenberg-Marquardt algorithm and one step secant, as well as testing the system. The test results showed the influence of each level, both when the output level of the previous positive or negative, were tested back at the next level. The effect indicates that the level above gives performance improvement and or strengthens the performance at the previous level.

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1. INTRODUCTION

The development of technology, making a lot of changes, especially a person's lifestyle. Information technology brings people into activities more easily, which is a lot of activities that can be done by just sitting behind a desk. The amount of change unhealthy lifestyle will have an impact on one's health [1]. Unhealthy lifestyle is one of the risk factors for coronary heart disease. A good anticipatory action is trying to make a healthy lifestyle and diligent to conduct a thorough medical examination to determine the presence or absence of blockage in artery coronary blood vessels. Unfortunately, such checks are expensive, and not every level of health services provided. Related to cost, a number of countries applying the concept of health insurance, such as in Indonesia with a national health insurance program (JKN). The concept of applying the concept of tiered JKN services, which are services of primary, secondary and tertiary [2]. Referring making it the medical examination should be conducted in phases.

The development of information technology, especially in the field of artificial intelligence, took effect in models of clinical decision support systems for the diagnosis of coronary heart disease. Numerous studies have been developed using artificial intelligence algorithms, such as C4.5 [3], [4], weighted association classifier [5], kNN [6], artificial neural network [7], [8], the fuzzy system [9] and the combination of classification and clustering [10]. The development of research on the system of diagnosis of coronary heart disease can be grouped into four. The first a diagnostic system without reducing the number of attributes. The second the system of diagnosis by reducing the attribute dimensions [11], [12]. The third

diagnostic systems are by the reduction of the attribute dimensions that consider the costs [13], [14], and the fourth diagnostic systems are by a tiered approach [15], [16].

The widely developed approach to heart disease diagnosis is focused on dimensional reduction combinations with artificial intelligence algorithms. The research with the theme of dimension reduction combination with consideration of cost and tiered approach is still relatively small. Several studies have proposed such a combination model, such as research conducted by Arjenaki et.al [13]. The study used a genetic algorithm with an element of the fitness function attribute inspection cost considerations. Artificial intelligence algorithms used to classify is naive Bayesian. A similar study conducted by Feshki & Shijani [14]. Only in the study using the particle swarm optimization for dimension reduction by the fitness function considering the cost of inspection attributes. Classification is done by using a feed forward neural network algorithm. The study also suggests grouping attributes investigation based on the costs. The method used in both studies, capable of reducing costly attributes in the diagnosis system of coronary heart disease.

The development of a further diagnostic model is to use a tiered approach. The model has not been widely developed. The concept of this approach is a common procedure used in the diagnosis process conducted clinician. This concept can be used for dimension reduction process, such as in studies conducted Wiharto et.al [16]. The grouping attribute research in accordance with the procedure clinician, for later analysis using a hierarchical of logistic regression algorithms. Attribute dimension reduction results, further classified by using artificial neural network algorithm. Referring to the grouping performed in research Feshki & Shijani [14], these studies also able to reduce costly attribute, with the system still provides a relatively good performance. Logistic regression algorithm is also used in research Abdar et.al [12], but the results generated dimension reduction there are two attributes costly, even if using the C5.0 algorithm is able to provide better performance.

Tiered approaches can be used to the model of diagnosis systems and dimensional reduction, as in a study conducted by Wiharto et.al [15]. The research uses fuzzy inference system algorithm, for its classification. The diagnostic system in the research is preceded by the rule extraction process using a C4.5 algorithm. Unfortunately in the study has not conducted a performance analysis that explains how much improvement and loss of system performance, for each addition of examination level. In addition, at the level of risk factor examination, the study used framingham risk score modeling to model fuzzy rule-based. If referred to in Kim et.al's study [17], under the use of framingham risk score is sometimes unsuitable for a particular country, this is due to the development of the model refers to a population in a particular country.

Referring to a number of studies that have been done, so in this study conduct performance analysis of each level, the model assessment of coronary heart disease with a tiered approach. Tiered approach refers to a commonly used procedure of clinicians in the diagnosis and the concept of a tiered system JKN services. Artificial intelligence algorithms that are used for each hierarchically using artificial neural network. The system is divided into three levels ANN system. At the first and the third level architecture ANN trained using the Levenberg-Marquardt algorithm, while the second level using the one step secant. Performance parameters analyzed were sensitivity, specificity, positive prediction value, negative prediction value, the area under the curve and accuracy at every level.

2. RESEARCH METHOD

2.1. Data

This study used the coronary heart disease dataset of the UCI repository, which can be accessed online [18]. Dataset consists of 13 examination attributes and 1 attribute conclusion examination, with the amount of data as much as 303. Dataset can be grouped based on inspection procedures consisting of three groups. The first group is risk factors, both modified and can not be modified, as shown in Table 1.

Tabel 1. Risk factor

Parameters	Category	No. (%)	Mean±SD
Age			54,439±9,0
Gender	1 : Men	206 (67,99)	
	0 : Women	97 (32,01)	
Diastolic blood pressure (mmHg)			131,69±17,6
Cholesterol in mg/dl			246,69±51,78
Fasting blood suger	1: > 120 mg/dl	45 (14,85)	
	0 : ≤ 120 mg/dl	258(85,15)	

The second group is chest pain type and ECG, which is the examination to determine the type of chest pain and cardiac electrical activity, both during rest and exercise, as well as maximum heart rate during exercise. A number of attributes and categories of inspection results as shown in Table 2.

Tabel 2. Chest pain type and electrocardiography (ECG)

Parameters	Category	No. (%)	Mean±SD
Chest pain type	1 : Typical Angina	23 (7,59)	
	2 : atypical angina	50 (16,5)	
	3 : non-anginal pain,	86 (28,38)	
	4 : asymptomatic	144 (47,52)	
Resting ECG	0: Normal	151(49,83)	
	1 : ST-T wave abnormal	4(1,32)	
	2 : Ventricular hypertrophy	148(48,84)	
Maximum heart rate achieved			149,61±22,88
Exercise induced angina	1 : Yes	99(32,67)	
	0 : No	204(67,33)	
ST depression induced by exercise relative to rest			1,04±1,16
The slope of the ST segment for peak exercise	1 : upsloping	142(46,86)	
	2: flat	140(46,20)	
	3 : downsloping	21(6,93)	

The third group is fluoroscopy and scintigraphy. This group consists of two types namely fluoroscopy examination to determine the number of blood vessels constrict, and scintigraphy to determine the type of defect that occurs. Attribute and category examination results are shown in Table 3. In addition, in Table 3 also contained the output attribute tests results showed normal or coronary artery abnormalities.

Tabel 3. Fluoroscopy and Scintigraphy

Parameters	Category	No. (%)	Mean±SD
Number of major vessels colored by fluoroscopy (0-3)	0 : Normal		
	1 : Single Vessel		
	2: Double Vessel		
	3: Tripple Vessel		
Defect type (Scintigraphy)	3 : Normal	166(54,79)	
	6 : fixed defect	18(5,94)	
	7 : reversible defect	117(38,6)	
Level Heart disease (0/1)	0 : Normal	164 (54,12)	
	1 : Abnormal	139(45,88)	

2.3. Artificial Neural Network

This study uses a multi-layer ANN architecture, using two types of training algorithm which Levenberg-Marquardt (LM) and one step secant (OSS). One step secant algorithm is a bridge between quasi-newton algorithm with the conjugate gradient. This algorithm does not store the complete hessian matrix. In the algorithm assumes that the previous Hessian matrix is the identity matrix so that the model change in weight that occurs in each iteration can be shown in Equation (1).

$$W_{k+1} = W_k - H_k^{-1} gW_k \quad (1)$$

where W_k is the weight values to k , H_k is the hessian matrix of the performance index weights the value of all k [19].

Artificial neural network with Levenberg-Marquardt training algorithm designed using the second derivative approach without having to calculate the hessian matrix[20]. The Hessian matrix can be approximated using Equation (2).

$$H = J' * J \quad (2)$$

Where J is the Jacobian matrix, which contains the first derivative of a network error to the weights, symbolized, e , while the slope can be calculated using Equation (3)

$$gW = J' * e \quad (3)$$

Weight improvement in LM algorithm can be expressed in an Equation (4) [21].

$$W_{k+1} = W_k - [J' * J + \mu * I]^{-1} * J' * e \tag{4}$$

If the value of $\mu = 0$, then this method is the same as the method of Newton, and if too large would be the same as the gradient descent with a very small learning rate.

2.4. Tiered Model of Assessment Coronary Heart Disease

Model assessment system of coronary heart disease is divided into three levels. The first level is the assessment of the risk factors, which consist of five attributes. The second level, an assessment of chest pain type and inspection electrocardiography (ECG), either at rest or exercise. Furthermore, the third level is an assessment by scintigraphy examination and fluoroscopy. Model assessment system of coronary heart disease by using the artificial neural network is shown in Figure 1. The tiered model adopts the procedures used by clinicians, and also the concept of tiered in JKN service system. When referring to the JKN system, in making a diagnosis of coronary heart disease, can not be served directly in the path of service JKN. The level of service that must be passed first is the primary service, the service can conduct an initial screening of coronary heart disease. If the positive screening results, then continue on the level of secondary services for further diagnosis for ECG examination, either at rest or exercise. If necessary, it can be examined as fluoroscopy and scintigraphy. The second type of examination the patient may only be served at the tertiary care level.

The tiered model of ANN shown in Figure 1, is divided into three levels, the first level of a risk factor, the second level of chest pain & ECG, and the third level of scintigraphy & fluoroscopy. In addition to the system is divided into three levels, the system is also divided into two stages of the process, namely the process of training and testing. The training process is done at each level to get optimal architecture of the artificial neural network. Training for the first and third levels using a Levenberg-Marquardt algorithm, while at the second level using one step secant algorithm. The resulting architecture in the training process is then used as a system model for assessment of coronary heart disease. Artificial neural network architecture uses two hidden layers, with the optimal architecture on the first level is 5-20-15-1. The architecture consists of 5 neurons in the input layer, 20 neurons in the first layer hidden, 15 neurons in the second hidden layer and 1 neuron in the output layer. In the second level, the architecture used is 6-30-25-1, while on the third level 2-20-15-1.

The proposed neural network architecture model uses a number of activation functions, firstly sigmoid bipolar (tansig) for the first hidden layer. The second is binary sigmoid (logsig) for the second hidden layer. The third is a linear function (purelin) for the output layer. The activation function is the same, both for training using a Levenberg-Marquardt algorithm and one step secan algorithm.

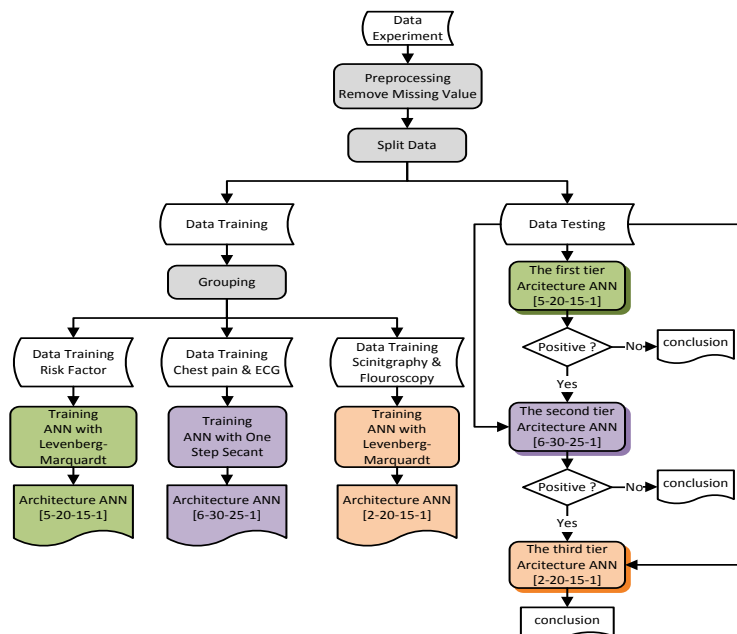


Figure 1. The proposed system model

2.5. Performance Analysis

Performance analysis of tiered assessment system model using artificial neural network consists of several performance parameters, namely sensitivity, specificity, accuracy, positive prediction value (PPV), negative prediction value (NPV), and under the curve (AUC) area. These parameters can be derived from the matrix confusion table shown in Table 4. The calculation Equations for each performance parameter as shown in (5-11).

Table 4. Confusion Matrics

Actual Class	Prediction Class	
	Positive	Negative
Positive	TP (True Positif)	FN (False Negative)
Negative	FP (False Positif)	TN (True Negative)

$$\text{Sensitivity} = \text{TP}_{\text{rate}} = \frac{\text{TP}}{\text{TP}+\text{FN}} \quad (5)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN}+\text{FP}} \quad (6)$$

$$\text{PPV} = \frac{\text{TP}}{\text{TP}+\text{FP}} \quad (7)$$

$$\text{NPV} = \frac{\text{TN}}{\text{TN}+\text{FN}} \quad (8)$$

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{FP}+\text{TN}+\text{FN}} \quad (9)$$

$$\text{FP}_{\text{rate}} = 1 - \text{TP}_{\text{rate}} \quad (10)$$

$$\text{AUC} = \frac{1+\text{TP}_{\text{rate}}-\text{FP}_{\text{rate}}}{2} [22] \quad (11)$$

]

3. RESULTS AND ANALYSIS

Tiered assessment system model testing carried out by using datasets from the University California Irvine (UCI) repository [18]. The dataset is dataset Cleveland's, with a distribution of data 178 for training and 100 for testing. The test results assessment system with tiered approach can be grouped into two parts. The first is a performance on each level, both the performance when the output at previous levels tested again at the next level, whether positive or negative output. The test results assessment system with a tiered approach can be shown in Table 5.

Performance test results for positive and negative output on the first tier, which was tested again on the second tier is shown in Table 6. The second is performance, the test results when the output, either positive or negative on the second tier, tested again on the third tier are shown in Table 7. The performance on the test pressing on parameter performance of sensitivity, specificity, and accuracy, determines the level of repairs and loss of the second and third tier.

Table 5. The performance of tiered artificial neural network

	sensitivity	specificity	PPV	NPV	AUC	Accuracy
The first tier	0,7872	0,4528	0,5606	0,7059	0,6200	0,6100
The second tier	0,6596	0,9434	0,9118	0,7576	0,8015	0,8100
The third tier	0,6596	0,9434	0,9118	0,7576	0,8015	0,8100

Table 6. The performance of the second tier

	Sensitivity	Specificity	accuracy
Positive	0,8378	0,8966	0,8636
Negative	0,9000	0,8750	0,8824

Table 7. The performance of the third tier

	Sensitivity	Specificity	accuracy
Positive	0,8065	0,6667	0,7941
Negative	0,6875	0,8600	0,8182

3.1. The Output Analysis of the First Tier then Examined at the Second Tier

The performance of tiered diagnostic system, can be analyzed its performance for each level, so it can know the influence of each level. The performance analysis is divided into two based on the test model. The first, when the first-level diagnostic system gives negative output, it is checked again at the second level. The second, when the diagnostic system gives a positive result at the first level, it is retested at the second level. The performance of the diagnostic system generated based on the two test models can be shown in Table 6.

Table 8. The confusion matrix of output negative of the first tier was tested on the second tier

Actual Class	Prediction Class		Actual Class	Prediction Class	
	Positive	Negative		Positive	Negative
Positive	37	10	Positive	9	1
Negative	29	24	Negative	3	21

(a)

(b)

To explain the performance between the first and second tier can be explained with reference to Table 8. Table 8(a) shows the confusion matrix output on the first tier. At the tier of the first negative output number of 34 patients, with details of 10 patients who should have been positive, but diagnosed negative, and 24 patients negative diagnosed negative. Tests come back on the second tier generate confusion matrix as shown in Table 8(b). Referring to the table can be a calculated improvement of the system, which is 10 patient that should be positive, able to be diagnosed positive number 9, so that the sensitivity of 90.00% as shown in Table 6. The sensitivity value also showed a performance improvement of 90% on the second tier, As for the negative patients, the second tier diagnosed negative return of 87.5% or a loss of about 2.5% at the second tier.

Table 9. The confusion matrix of output positive of the first tier was tested at the second tier

Actual Class	Prediction Class		Actual Class	Prediction Class	
	Positive	Negative		Positive	Negative
Positive	37	10	Positive	31	6
Negative	29	24	Negative	3	26

(a)

(b)

Further analysis to the output of the first tier positive, were retested on the second tier. To analyze the performance on these tests, carried out by using the table just as the confusion matrix shown in Table 9. Output positive on the first tier amounted to 66 patients, consisting of 37 patients diagnosed positive and 29 negative patients diagnosed positive, just as shown in Table 9(a). The test results back on the second tier, as shown in Table 9(b). These results showed an improved performance, ie patients by the first tier should have been a negative but positive diagnosis, the 29 patients, the second tier is able to be diagnosed to be negative as many as 26 patients. The improvement in the amount of specificity as shown in Table 6, which is 89.66%. In this test also there is a loss, ie 37 positive patients who were diagnosed positive by the first tier, re-diagnosed positive by the second tier of 31 patients. It shows the occurrence of a loss of 1-sensitivity, or by 16.22%. The loss value is greater than the loss that occurs when testing negative (healthy).

3.2. The Output Analysis of the Second Tier then Examined at the Third Tier

The test result when the output at the second tier, tested again on the third tier, the resulting performance parameter values, namely sensitivity, specificity, and accuracy, can be shown in Table 7. Test on the third tier, performed well when the output the second tier negative and positive. To be able to analyze in more detail, we can see the performance for each output. First for output the second tier negative, which

will be tested again on the third tier, the resulting confusion matrix as shown in Table 10. Table 10(a) shows that the output at level 2, comprising 16 patients positive but negative detected and 50 patients with negative and negative detected. The test results come back negative output at level 2, were tested back on the third tier, are shown in Table 10(b). Output at the third tier indicates a performance improvement of sensitivity value, ie 68.75%. The resulting improvement is lower than when the output tested negative on the second tier. Besides an improvement, on the third tier also occur relatively large loss, which amounted to 1-specificity, ie 14.00%.

Table 10. The confusion matrix of output negative of the second tier was tested at the third tier.

Actual Class	Prediction Class		Actual Class	Prediction Class	
	Positive	Negative		Positive	Negative
Positive	31	16	Positive	11	5
Negative	3	50	Negative	7	43

(a) (b)

The second test is when the output of the second tier is positive and was further tested at the third tier. To explain the performance of the system can be done by using Table 11. The output of the second tier consisted of 31 patients positive undiagnosed positive and 3 patients negative undiagnosed positive. Improvement of system performance at the third tier indicated by its specificity, ie 66.67%, and there is a loss of 1-sensitivity, ie 19.53%. At the third tier, both for positive and negative output suffered only relatively little improvement, but there is a loss of relatively large, compared to the performance at the second tier.

Table 11. The confusion matrix of output positive of the second tier was tested at the third tier

Actual Class	Prediction Class		Actual Class	Prediction Class	
	Positive	Negative		Positive	Negative
Positive	31	16	Positive	25	6
Negative	3	50	Negative	1	2

(a) (b)

The test results at the third tier, shows a relatively large loss occurs, but balanced with a relatively high improvement. These conditions make the performance at the third tier not relative give improvement of output at the second tier. This can be shown in Table 5, where the value of performance parameters does not change. By value, it reinforces the test at the second tier, but not so when analyzed for each data, as described in the analysis in Table 10-11, it means that there are some improvement and some loss.

3.3. Analysis tiered model performance ANN

Performance assessment tiered system with ANN, the first tier is able to provide sensitivity value of 78.72%, as shown in Table 5. This value indicates that when patients declared positive, the system is expressed strongly positive with a percentage of 78.72 %, whereas when the patient is declared negative, the system actually declared negative by the percentage of the value of specificity, ie 45.28%. Performance diagnosis system on the first tier is a prediction based on risk factors. This is compared to the research conducted by Kim et.al [17], the proposed system has better performance. The performance in research Kim et.al [17], when using algorithms ANN, parameter sensitivity performance of 73.10%, while 43.59% specificity. Still, in the same study, the proposed system is better compared using logistic regression algorithm and C5.0. It is different when compared to the use of ANN in research Yang. et.al [23], the performance on the first tier is relatively lower. In research Yang et.al [23], the resulting performance parameters sensitivity of 85.7%. The high sensitivity and specificity performance in research Yang et.al [23], one of the factors due to the number of attributes that are used in the diagnosis more, compared to the system proposed.

Assessment system at the second and the third tier have a similar performance, which means that checks on the third tier reinforce checks on the second tier, that if only limited attention to the performance parameter value. The movement of the patient changes when tested at the second tier and tested at the third tier, for the output positive of the previous tier can be viewed in detail in Table 10-11. Accuracy performance parameters for the second tier reached a value of 81.00%, the performance is better than a tiered approach in research Wiharto et.al [15], which only reached 75.42%. Research Wiharto et.al [15] using a tiered concept

that is implemented with fuzzy inference system (FIS), which preceded his rule-making algorithm C4.5. When compared to other studies, which both use ANN, such as in research Wiharto et.al [16], parameter accuracy performance of the proposed system is relatively lower. It's just that there are differences in the application of its tiered concept, the proposed system is used in making the diagnosis, whereas in the study Wiharto et.al [16] using a tiered concept to perform reduction of attributes dimensions.

4. CONCLUSION

An assessment system model with a tiered approach using ANN, able to provide improvement and strengthening performance for each increasing of level. The resulting performance at the second tier with the attribute consisting of the risk factor, chest pain type and ECG able to give 81.00% accuracy performance. The performance is better than a number of previous studies. Especially at the third level shows the balance of repairs and loss, so the performance at the third tier is relatively the same with the performance at the second tier, or can be seen by the value of performance parameters occurred the strengthening of the previous ladder.

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